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WEED CLASSIFICATION FROM PADDY CROPS USING CNN

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ABSTRACT:
The eradication of weeds is vital for the successful cultivation of crops, although identifying and eliminating weeds in a paddy field poses challenges. Weeds have similar characteristics with crops, including color and form. The advancement of artificial intelligence has paved the way for improved detection and categorization of weeds in paddy crops, leading to higher agricultural yields. Conventional methods of weed control include the use of pesticides, which may have harmful effects on the environment. The proposed approach involves using the Convolutional Neural Network technique to classify many types of weeds in the specific region of Vriddhachalam, Tamil Nadu, India. Additionally, a heterogeneous model is constructed and the performance and accuracy of the prediction are compared. The collected datasets are processed, and a deep neural network model is used to categorize several species, such as Ammania Baccifera, Centella Asiatica, Commelina Benghalensis, Chloris Barbata, Cynodon Dactylon, Echinchloa Colona, and Echinochloa Crus-galli.

An analysis is conducted to examine the effectiveness of deep neural network models by exploring different batch sizes, epochs, and hyper-parameter adjustments. The CNN and heterogeneous models exhibit reliability rates of 97.13% and 96.93%, respectively, in weed classification. Applying deep neural networks to weed categorization and detection will enable precise weed control and sustainable production. This proposed study showcases accuracy in identifying the target location.

Keywords: Convolutional neural network, Deep learning, Hyper-parameters, Pesticides, Weed categorization.

I. INTRODUCTION

Rice is a crucial grain that is widely used and relied upon as a staple food in the diets of many people. This dependence is extensive globally and is crucially relevant in several Asian countries. Currently, the automation level in rice production is lower compared to other major global staple crops such as wheat, maize, or sorghum. These crops are cultivated in vast regions using efficient techniques, large machinery, and mass production. In contrast to these crops, rice production continues to need highly skilled human labor.

Fitch et al. [1] examine how the use of automation and agent-oriented frameworks might enhance the efficiency and production of agriculture. Farming, being the primary source of food, sustenance, fiber, and fuel essential for human survival, has the distinction of being the oldest and most significant economic activity throughout human history. By 2050, the global population is projected to reach around 9 billion, necessitating a doubling of agricultural output to meet the increasing need for food and bioenergy. To reach this objective, it is predicted that agricultural output must rise by 25% while minimizing the environmental impact, given the restricted resources of labor, water, and transportation. Automation is essential for society to fulfill the needs of the rural population by 2050.

An important problem with traditional cropping systems is the excessive development of unwanted plants or weeds. This reduces the productivity and quality of farms because these plants compete with crops for resources such as water, light, space, and soil nutrients [2, 3]. Globally, it was projected that pests might result in losses ranging from 40% to 80% in 2019. The estimated production losses caused by weeds were found to be around 34%, making it the most among all pests. However, the extent of loss varies depending on the specific crops. Therefore, it is crucial to use more effective techniques of controlling weeds in order to sustain agricultural productivity.

Chemical pesticides are often used as a primary method for managing weeds. According to [5], almost 60% of pesticides produced worldwide are herbicides designed to decrease the development of weeds.

Although herbicides enable farmers to effectively manage weed infestations and achieve higher production, their use should be restricted owing to the adverse effects of herbicide chemicals on the environment, human health, and other organisms. Repeated application of the same herbicides in a field leads to the proliferation of weed species that are resistant to the herbicides. According to Panozzo et al. [6], there are 450,000 places worldwide that have 365 herbicide-resistant biotypes. These biotypes belong to 200 species, with 115 being dicots and 85 being monocots. This information aligns with the comprehensive insights provided on Herbicide Secure Weeds. Reliable sprinkling is often considered the most popular method for applying herbicides [7]. However, this method is inefficient and ineffective since weeds are often distributed unevenly and concentrated in clusters or patches inside the cultivated land [8, 9]. There are some areas inside the field where neither weeds nor a significant amount of them are present.

Site-specific Weed Management involves the targeted administration of herbicides to particular areas of a field that are plagued with weeds. This approach may reduce the overall amount of herbicides used in post-emergence treatments. Unique and targeted herbicides are used with varying treatment rates in particular locations to manage both broadleaf and grass weeds in an unconventional approach [10]. Under these conditions, Automated targeted herbicide applications may enhance the effectiveness and dosage of herbicides by applying an advanced image mapping technique to accurately detect the local distribution of broadleaf and grass weeds. Furthermore, it is more practical to classify weeds into broadleaf and grass categories rather than classifying them based on their specific species, since this classification method [11] provides computational feasibility and aligns with existing pesticide usage [12]. This study focuses on the identification and detection of weeds in paddy fields using a CNN classification method based on area, as well as the suggested CNN classification method for real-time photos. The process flow of the weed categorization is shown in Figure 1. The gathered photos will undergo canny edge detection after being Gaussian blurred. Next, the categorization based on area is analyzed in the following manner. Section 2 covers the related work, section 3 focuses on image pre-processing, section 4 provides detailed information on the convolutional neural network used for area-based classification and the proposed classification method, section 5 discusses the results, and section 6 concludes the study.

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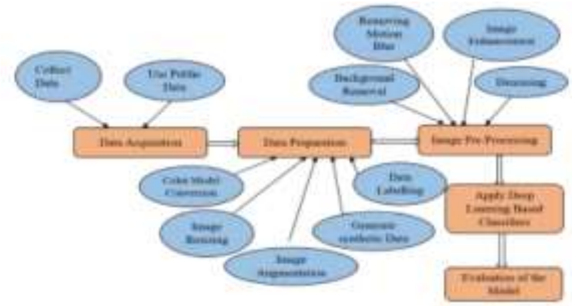

Fig. 1.Weed classification pipeline.

II. LITERATURE SURVEY

Machine Learning (ML) and Deep Learning (DL) techniques have been applied to weed detection, identification, and management. Brown and Noble [13] looked into ground-based area methods and blocked off weed mapping. They moreover went into length on the confinements of distinguishing weeds in crops utilizing either morphological or geological subtle elements. Concurring to their thinking, it is best to create utilize of both highlights.

Di Mauro et al. [14] examined 10 principal components and potential boundaries to building a completely independent mechanical weed administration technique. Various agricultural problems and their related challenges such as weed detection and identification was addressed by Merfield [15] and reported the outperformance of Deep Learning techniques than the conventional methods of image processing. The foremost troublesome perspective of a weed disclosure methodology, concurring to Kamilaris et al. [16], is separating between weed and crop species. They centred on a few machine vision and image handling strategies utilized for ground-based weed location.

III. IMAGE PRE-PROCESSING

A fascinating edge location algorithm that manages with noise in a picture has been demonstrated by Canny. He focused on three important elements in his strategy. The calculation must first locate each of the essential edges. Second, he emphasized that there should be little difference between the edge's true position and its discovered position, and third, there should only be one response to each edge [17]. Canny edge detection algorithm was chosen since the edge image it produces is essentially superior and more precise than those delivered by other calculations. In expansion, the channel parameter as well as the parameter for the two edges utilized for thresholding hysteresis can be adjusted in understanding with the dissent interior the picture to deliver the ideal edge picture [18]. By taking these steps, hysteresis utilizes these edges; in case the estimate is underneath the essential restrain, it is set to zero (made a non-edge). Within the impossible occasion that the estimate is more noteworthy than the tall edge, it is made as an edge. The pre-processing steps adopted respective process in this research, and they are depicted in Fig. 2.

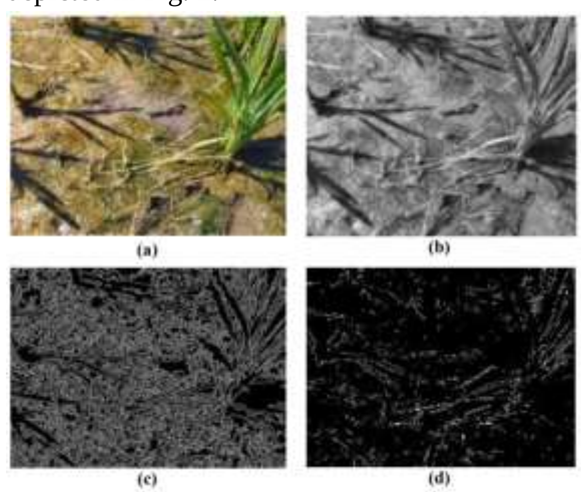

Fig. 2. Pre-processed images (a) Original Image (b) Gaussian blurred image (c) canny edge detected-Mid range threshold (d) canny edge detected- Tight threshold.

IV. CONVOLUTIONAL NEURAL NETWORK

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For the common cultivating application appeared within the introduction, the utilized CNN ought to as it were be able to recognize the pixel and determine if it may be a paddy crop plant or weed. In Fig. 3, a block diagram of CNN based weed classification is shown. It has eleven layers and employments an RGB picture with an input measure of 101 by 101 pixels. The abdicate method of reasoning can distinguish between two classes (weed and paddy crops). 16 highlights are shown within the essential layer after the input layer, with an assessed estimate of 5 5 pixels. Take 32 highlights that are 7 x 7 pixels in measure at that point.

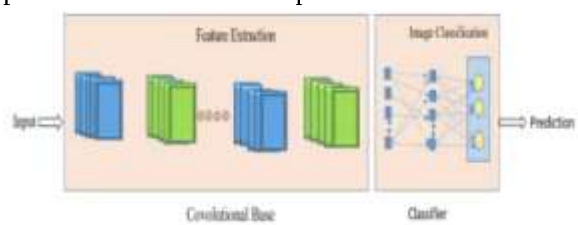

Fig. 3. Block Diagram of CNN based weed classification.

There are 32 highlights with an evaluated measure of 5 5 pixels after the pooling layer. The 64 highlights within the last convolution layer have a degree of 7 × 7. A pooling layer, taken after by three dense layers, each with a size of 64 features, comes taking after the convolution layer. There are three neurons within the output layer. Subsequently, three classes can be distinguished (paddy crops, weed and establishment).

An entire input picture must first be divided into 101 × 101 pixel sections for categorization. The core pixels of each of these components are then categorised separately, and so on, handling the entire image. The identical calculations are repeated numerous times by dividing the image into 101 × 101 pixel sections. The thick layer, in a sense, causes the separation into 101 × 101 pixel sections. This spares a significant chunk of the calculations. As a result, the first feature value in the Convolution Layer is multiplied by the first feature with the entire input image and stored within the feature-map. The second Convolution Layer also affects the feature maps that includes the entire picture at the moment. Thus, the Dense Layer receives the entire input image's data. The input picture is then divided into 101 × 101 large sections by this layer. Here the classified image shows the paddy crops are in green and the weeds are red in colour. Dong et al. [19] proposed a semisupervised Double Deep Q-Network (SSDDQN) for abnormal traffic detection. It leveraged deep reinforcement learning and auto encoders to handle highdimensional data and reduce labelling costs. Zhu et al. [20] explored the link between root morphology/physiology and rice grain quality and the importance of these parameters which requires the appropriate tuning of the parameters and would lead to increase the computation time. The proposed model involved the hyper parameter tuning by adopting k-fold cross validation, the split applied here is 3 for detecting the images. The weed detection on the real time images has given better accuracy after applying the k-fold cross validation.

V. RESULTS AND DISCUSSION

The dataset comprises of 1652 plants, of which 50% are weed and 50% are paddy crops in the primary and secondary data individually. Validated the model with the real time data obtained from the field to detect the weed. Also, the set incorporates a variation in the time period, different climate influences, and numerous formative stages of crop. The evaluated results are shown in the Fig. 4.

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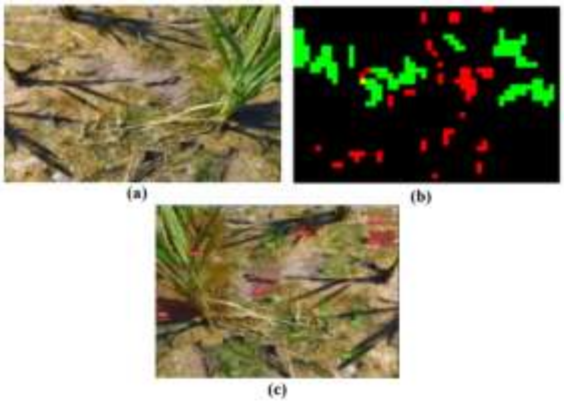

Fig. 4. Proposed work (a) original image (b) Area based classification-CNN (c) Real time Weed detection.

Table 1 presents the classification results of proposed work on the primary and secondary datasets. In terms of differentiation, we obtained 95.23% accuracy using the Area based classification and 96.12% for the proposed model. These results showed that the hyper parameter tuning would give even better performance with different techniques. From the obtained results and process carried out it is suggested that tuning will help in improving the framework's performance, with a focus on classifier development. Additionally, new images and image types will be created and tested in order to determine the best model for a smart weed detection and categorization.

Table 1. Model performance.

Dataset	Parameter	CNN	
		Area based	Proposed
Secondary data (collected from open sources)	Accuracy	83%	85%
	Training Time	27 min	23 min
Primary data (obtained from paddy field)	Accuracy	95.23%	96.12%
	Training Time	29 min	28 min

VI. CONCLUSION

This study demonstrated the essential procedures for managing photographs in the context of plant and weed categorization. The accuracy score is used to assess and validate the model's performance on both the main and secondary datasets. The CNN model, after hyperparameter adjustment, achieved an accuracy of 96.12% in accurately recognizing weeds and paddy. The classifiers were meticulously evaluated using accurate measurements. Various climatic factors and other environmental components are also considered. Although the suggested Convolutional Neural Network classifier yields exceptional classification outcomes.

This classifier has exceptional potency and demonstrates superior speed in execution.

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